Renewable and Sustainable Energy Reviews 15 (2011) 665–672

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

Integration of CCS, emissions trading and volatilities of fuel prices into sustainable energy planning, and its robust optimization

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ARTICLE INFO

Article history:
Received 14 May 2010
Accepted 19 July 2010

Keywords:
Energy planning
Renewable energy
Carbon capture and storage
Robust optimization
Uncertain environment

ABSTRACT

In this paper, a new approach has been proposed that allows a robust optimization of sustainable energy planning over a period of years. It is based on the modified energy flow optimization model (EFOM) and minimizes total costs in planning capacities of power plants and CCS to be added, stripped or retrofitted. In the process, it reduces risks due to a high volatility in fuel prices; it also provides robustness against infeasibility with respect to meeting the required emission level by adopting a penalty constant that corresponds to the price level of emission allowances. In this manner, the proposed methodology enables decision makers to determine the optimal capacities of power plants and/or CCS, as well as volumes of emissions trading in the future that will meet the required emission level and satisfy energy demand from various user-sections with minimum costs and maximum robustness. They can also gain valuable insights on the effects that the price of emission allowances has on the competitiveness of RES and CCS technologies; it may be used in, for example, setting appropriate subsidies and tax policies for promoting greater use of these technologies. The proposed methodology is applied to a case based on directions and volumes of energy flows in South Korea during the year 2008.

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doi:10.1016/j.rser.2010.07.050

1. Introduction

The introduction and advancement of renewable energy technologies have made energy planning a more complex task with higher chances for a greater sustainability. Availabilities of renewable energy sources (RES) such as solar photovoltaics, wind power, and biomass have not only broadened means to generate electricity, but also made it possible to reduce emission of greenhouse gases (GHG). As a result, decision makers in energy planning can now pursue multiple objectives that include satisfying energy demand, minimizing costs, and meeting the required and/or agreed GHG emission level [1].

Such changes in objectives and employable technologies have transformed energy planning into a different problem such that traditional methodologies can no longer provide an optimal solution to decision makers. Consequently, new methodologies have been studied and proposed. Among the different types, optimization schemes have been widely implemented for their effectiveness in providing desirable results under varying conditions [2,3].

Optimization schemes in energy planning can be distinguished according to the models they adopt and techniques they employ in finding an optimal solution. In terms of models, schemes have adopted the time-stepped energy system optimization model (TESOM), market allocation model (MARKAL), energy flow optimization model (EFOM), or inexact community-scale energy model (ICS-EM); various linear programming methods such as interval linear programming (ILP), chance-constrained programming (CCP) and mixed integer linear programming (MILP) techniques have been employed to solve these models [1,2,4]. Each model successfully reflects certain characteristics of the problem that previous works could not incorporate into an optimal solution (Table 1). For example, EFOM has been modified by Cormio et al. such that the privatization of the most important energy sectors, greater interest towards distributed generation technologies based upon renewable energy sources (RES), and localization of energy planning activities are reflected in an optimal plan [1]. On the other hand, Cai et al. has developed an ICS-EM in order to incorporate uncertainties associated with dynamic changes of system conditions, especially temporal and/or spatial variations of renewable energy resources [2].

Despite the successes of previous methodologies, the following aspects of energy planning still need to be incorporated for greater practicality and effectiveness of an optimal solution [5–8]:

- Uncertainties in prices of fossil fuels; as alternatives in generating electricity, fossil fuels' prices directly affect the competitiveness of RES; their high volatility requires more than deterministic assumptions in finding an optimal plan with respect to cost-effectiveness.
- Expansion of emissions trading; greater parts of the global economy are now participating in emissions trading, and consequently, additional revenues coming from using RES or financial burden of not meeting the required GHG emission level need to be incorporated in modeling their economics and costs.
- Possibility of retrofitting carbon capture and storage (CCS) in coal plants that can also reduce CO_2 emissions while providing electricity.

This paper aims to provide a methodology that can incorporate these recent changes in nature of sustainable energy planning and generate an optimal plan in an uncertain environment. It attempts to do so by adopting following methods and techniques in modeling and solving the problem. To begin with, a traditional EFOM is modified such that cost structures of power plants include revenues or financial burden due to emissions trading. In addition, installation of CCS in coal plants is also included as one of alternatives in the energy supply sector. Lastly, a robust optimization technique is adopted in generating an optimal plan such that its robustness under an uncertain environment with identifiable scenarios is guaranteed [9]. A case study is given to demonstrate the applicability of the proposed methodology.

2. Modifications to the EFOM

The EFOM models energy systems as networks of energy flows that connect energy produced from the supply sector to end-users who consume converted and transported amounts [1,2,10]. In the process, excess or lacking energy can be sold or bought by interacting with external energy grids. Environmental impacts of energy systems such as emissions are also incorporated as external costs. Within these networks, planning is made over the horizon of time that is divided into a certain number of periods; an optimal plan is found that minimizes the total present cost of the entire energy system in the presence of equality and inequality constraints such as peak demand satisfaction and limits on RES potentials.

In the proposed methodology, the EFOM is modified from the previous status [1] as depicted in Fig. 1. As one may notice, three types of modifications have been made in terms of employable energy technologies, emissions trading, and availability of CCS.

2.1. Employable energy sources

Multiple sources and technologies can contribute in supplying energy to end-users. Employable energy sources may vary with respect to changes in a region's geographic, social, economic, and/or technological conditions. For example, four types of energy sources—fossil fuels, renewables, and industrial byproducts such

Table 1
Characteristics of previous energy planning models and corresponding optimization techniques.

Model	Description of the model	Optimization techniques
TESOM	(1) Optimizes energy system planning over a sequence of single-periods (2) Models a single-region based energy system	LPs
MARKAL	(1) Integrates supply and demand sectors into the whole system that include production, conversion, processing, transmission and utilization steps (2) Large-scale, technology-oriented energy-activity model	LP
EFOM	(1) Splits energy sectors into sectors for supply, conversion, and usage (2) Takes into account environmental concerns with respect to RES and cogeneration by employing external costs in the objective function (3) Restricts the planning activity to a regional scale	LP
ICS-EM	(1) Employs a modular structure of multiple components: sources, technologies, sectors, and processes (2) Incorporates uncertainty consideration into the formation of optimization problem, especially the spatial and/or temporal fluctuations of RES (3) Can reflect dynamic changes in social, economic, legislative and resource-conditions	ILP CCP MILP

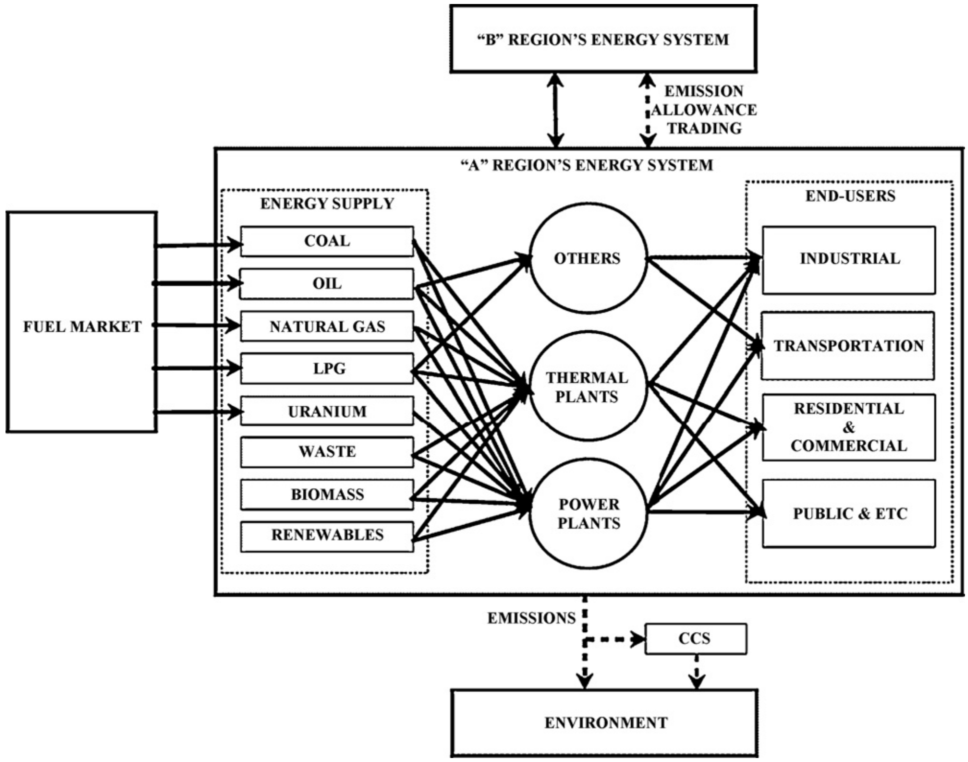

Fig. 1. The modified EFOM for the proposed methodology.

as blast furnace and cokery gas—are included in the model developed by Cormio et al. [1]. In the proposed methodology, the list is expanded by adding nuclear power as another primary energy source that can be employed; this is due to the fact that nuclear power plants are gaining greater attention as one of sustainable energy sources, and that they are already responsible for a substantial portion of numerous regions' energy supply (e.g., 33.6% in South Korea for the year 2008) [11,12]. In addition, fossil fuels are categorized into coal, oil, and natural gas so as to set individual prices for each; it is necessary in solving the planning problem with a stochastic programming method.

2.2. Emissions trading

In 2003, the European Parliament and Council commenced a CO_2 emission allowance trading scheme (EU ETS) within their community [7]. Since then, greater parts of the world have joined, or are planning to join the efforts; as a result, cashflows and thus economics of power plants have become dependent also on how much emission is made during their operation, and the price of emission allowance. This requires a modification in modeling an optimization problem for energy planning since costs have been regarded as one of the most important factors in objective functions [1–4]. In the proposed model, the modification is made such that emission allowances can be traded between different regions; for simplicity of modeling, it is assumed that trading can take place of any size on an annual basis.

2.3. Availability of CCS

CCS technologies have the potential as a promising solution to the problem of reducing GHG emissions in generating electricity. Various countries around the world are considering a large-scale implementation of CCS in their coal plants. For example, in Korea, Maritime and Ocean Engineering Research Institute has carried out researches on offshore underground geological storage of CO_2 since 2005 [13]; in the UK, the government is looking for a candidate so as to support a project that will install a post-combustion CCS of 300–400 MW [14]; the US government is sponsoring a program that aims to develop fossil fuel power plants with over 90% CO_2 capture technologies [8]. In this manner, some expect CCS to be responsible for up to 55% of collective efforts towards reducing GHG emissions by 2100 [15].

The degree to which CCS is employed in generating sustainable energy will depend on both internal and external conditions. Internally, its performance effectiveness and economics will be the key factors. In this regard, one of the most recent findings by Rubin et al. reported that CCS is able to capture 87–88% of CO_2 emission with 16–66% increase in costs per electricity produced [16]. External conditions that affect demand of CCS include emission-reduction target, unit price of emission allowance, and economics of RES technologies that directly compete with CCS in providing sustainable energy.

3. Mathematical programming of the modified EFOM

Based on the modified EFOM, a mathematical programming has been developed. It differs from the previous models (Table 1) in the manner described. The following subsections will demonstrate how these differences are incorporated in mathematical terms at each part of the programming—objective function, inequality, and equality constraints.

3.1. Objective function

In the proposed model, the ultimate goal has been set as a robust optimization of total costs in energy planning and management. Consequently, the objective function consists of variables that represent various types of costs that arise in the activity; it consists of investment (CI), fixed (CF), and variable (CV)

costs as follows:

$$\mathrm{CI} = \sum_{t=1}^{Nt}\sum_{u\in U}(\mathrm{IC_u}\cdot \mathrm{SA_{u,t}} + \mathrm{IS_u}\cdot \mathrm{SS_{u,t}} + \mathrm{IR_u}\cdot \mathrm{SR_{u,t}}) \quad (1)$$

$$\mathrm{CF} = \sum_{t=1}^{Nt}\sum_{u\in U}[\mathrm{FC_u}(\mathrm{SA_{u,t}} - \mathrm{SS_{u,t}})] \quad (2)$$

$$\mathrm{CV_s} = \sum_{t=1}^{Nt}\sum_{f\in F}(\mathrm{PF_{s,f,t}}\cdot \mathrm{VB_{f,t}}) \quad (3)$$

Eq. (1) is total investment costs: $\mathrm{IC_u}$ and $\mathrm{IS_u}$ represent unit costs for adding and stripping power plants of type u while $\mathrm{IR_u}$ refer to the unit cost retrofitting CCS in coal plants ($/MW); $\mathrm{SA_{u,t}}$, $\mathrm{SS_{u,t}}$, and $\mathrm{SR_{u,t}}$ stand for capacity of plants added, stripped or retrofitted (MW). Eq. (2) is the total fixed costs arising from maintaining and operating existing plants, with $\mathrm{FC_u}$ representing the unit fixed cost for plant of type u ($/MW). Lastly, Eq. (3) is the total variable costs that come from purchasing fuels: $\mathrm{PF_{s,f,t}}$ is the price of fuel f under the scenario s ($/TOE) while $\mathrm{VB_{f,t}}$ is the volume of fuel f bought in year t (TOE).

From these equations, the following objective function is built that incorporates additional terms for a robust optimization of total costs [9,17]:

$$\begin{aligned}\min \mathrm{CT} = &\sum_{s\in S} p_s(\mathrm{CI}+\mathrm{CF}+\mathrm{CV_s}) \\ &+\lambda\sum_{s\in S} p_s\left[\mathrm{CI}+\mathrm{CV}+\mathrm{CV_s} - \sum_{s'\in S'} p'_s(\mathrm{CI}+\mathrm{CV}+\mathrm{CV_s}) + 2\theta_s\right] \\ &+ w\sum_{s\in S}\sum_{t=1}^{Nt} p_s \mathrm{VT_s}\end{aligned} \quad (4)$$

The first term computes a mean value of total costs while the second term measures the variance; the third term measures model robustness with respect to infeasibility associated with the control constraint (5) under scenario s. In this sense, the parameter λ represents decision makers' sensitivity with changes in the data under all scenarios; w measures their willingness to trade between the robustness of solution and model [17].

3.2. Constraints

3.2.1. CO_2 emission requirement

$$\sum_{u\in U}[\mathrm{ER_u}(\mathrm{SA_{u,t}} - \mathrm{SS_{u,t}} - \mathrm{SR_{u,t}}) + \eta\cdot \mathrm{ER_u}\cdot \mathrm{SR_{u,t}}] - \mathrm{VT_{s,t}} = \mathrm{ET_{s,t}} \quad (5)$$

In Eq. (5), $\mathrm{VT_{s,t}}$ stands for the volume of emissions trading while $\mathrm{ET_{s,t}}$ represents the emission requirement level in year t under scenario s (tonne); $\mathrm{ER_u}$ is the emission rate of plant u (tonne/MW) and η is the emission-reduction coefficient of CCS-installed power plants (e.g., $\eta = 0.9$ means that CCS can reduce 10% of CO_2 emission rate). It is a control constraint that determines the volume of emissions trading necessary to meet the emission requirement level in year t under scenario s. A positive $\mathrm{VT_{s,t}}$ implies that the volume of CO_2 emitted in year t has surpassed the required level and that allowance be bought for meeting the target level. Similarly, a negative value means that emission allowance can be sold to reduce total costs.

3.2.2. Limits on RES potentials

$$\sum_{t=1}^{Nt}(\mathrm{SA_{u,t}} - \mathrm{SS_{u,t}}) \le \mathrm{SL_u} \quad \text{for u = RES-based power plants} \quad (6)$$

Eq. (6) sets limits, $\mathrm{SL_u}$, on capacities of RES-based power plants with respect to natural and/or technological conditions of a particular region where they are to be installed (MW). In dealing with capacities of RES-based power plants, it is important to note that the proposed model does not take into account their dynamic availabilities with respect to time. While Cai et al. have put an emphasis on the uncertainty involved in this issue [2], the proposed methodology has adopted a different approach by taking an assumption that RES-based power plants will be constructed in hybrid systems such that stable supply of energy is made possible regardless of the time of day or season. Such an assumption is based on recent improvements in hybrid technologies: a hybrid solar PV and hydrogen system has been simulated, built and tested by numerous institutions around the world [18,19]; wind–fuel cell hybrid energy systems have also been studied extensively by researchers [20,21]. In taking this assumption, investment and fixed costs for RES-based power plants are modified to include additional costs due to hybridization.

3.2.3. Limits on CCS retrofittability

$$\sum_{t=1}^{Nt}\mathrm{SR_{u,t}} \le \sum_{t=1}^{Nt}(\mathrm{SA_{u,t}} - \mathrm{SS_{u,t}}) \quad \text{for u = coal plant and } t = 1,\ldots,N_t \quad (7)$$

Eq. (7) restricts the capacity up to which CCS can be retrofitted in coal plants: the total capacity of CCS retrofitted cannot exceed the sum of capacities of remaining coal plants.

3.2.4. Energy demand satisfaction

$$\sum_{u\in U}\left[\frac{1-\kappa}{\nu}(\mathrm{SA_{u,t}} - \mathrm{SS_{u,t}})\right] \ge \Psi\cdot\sum_{n\in N}[(1+\rho)^t\cdot \mathrm{VD_{n,t}}] \quad \text{for } t = 1,\ldots N_t \quad (8)$$

Eq. (8) requires the planning and management system to provide energy enough to meet the sum of demand from each user section, $\mathrm{VD_{n,t}}$ for every year (TOE). In computing the volume of demand, two factors have been adopted: ρ represents the annual rate at which demand increases while ψ is the target level greater than or equal to which energy will be supplied. As a result, it is possible to build capacities to meet, for example 70% of the aggregate demand, as well as 125% of the volume: the former will most likely be useful to decision makers with limited budget while the latter will be of value for ones with abundant budget. Meanwhile, the volume of energy generated from existing power plants is computed with consideration of loss factor κ that takes place due to transmission loss and internal use of electricity in power plants; ν is the conversion ratio from MWh to TOE.

3.2.5. Primary energy mass balance

$$\mathrm{VB_{f,t}} - \sum_{u\in U_f}\left[\frac{1}{\nu}(\mathrm{SA_{u,t}} - \mathrm{SS_{u,t}})\right] = \mathrm{VR_{f,t}} \quad (9)$$

Eq. (9) makes sure that primary energy mass balance is kept in the system. In doing so, decision makers can decide on how much volume of fuel f they want to keep as safety stock at the end of year t, as represented by the term $\mathrm{VR_{f,t}}$. In response, the volume of fuel $\mathrm{VB_{f,t}}$ necessary to purchase in that year is determined. It is worthwhile to note that the proposed model does not allow selling domestically produced fuels to markets for profits; however, a slight modification to Eqs. (1) and (9) can make it possible to add the option of selling.

The set of equations defined in this section can be computed by using commercially available software programs like LINDO or GAMS. The following case study has been solved by GAMS with CPLEX that can generate solutions for MILP.

4. Case study

In this section, a sample application of the proposed methodology is presented to illustrate its applicability and effectiveness. The sample case is based on sustainable energy planning in South Korea from the year 2008 to 2020.

4.1. Case description

In the year 2008, the South Korean peninsula consumed a total of 385,070,137 MWh (Fig. 2) [22]. The industrial section was responsible for the largest volume, which sums to 53.6% of the total; the residential and commercial users ranked the 2nd with the net spending of a volume worth 41.6%; the public, etc. section came third by consuming approximately 4.6%; the transportation utilized the least that equals to 0.2% of the net consumption, in terms of electric energy generated by power plants. Meanwhile, the net generation of energy from power plants summed to a total of 422,355,126 MWh (Fig. 2) [22]. 35.1% of the energy had been generated by coal plants; nuclear power plants also contributed a substantial volume worth 33.7% of the total; gas and oil plants came next with 18.9% and 11.5%, respectively; four types of RES-based power plants (hydro, solar PV, wind, and biomass) generated a net volume worth 0.9%.

South Korea has long been a net importer of primary energy sources, especially fossil fuels. Consequently, the government has had profound interests towards RES, and supported numerous research and commercialization efforts on RES-based power plants [11,22]. In this sense, CCS has also gained attention. In fact, the economic and environmental impacts of retrofitting it to different types of fossil fuel plants have been studied extensively under the LEAP (long-range energy alternative planning) model [23]; accordingly, CCS with O_2/CO_2 recycle is the most economical and may contribute the most by being retrofitted to coal plants.

Under the aforementioned conditions, decision makers are challenged to decide on the following variables for the coming years until 2020: capacities of power plants and/or CCS to be installed in each year, and their respective types. In doing so, they are required to minimize costs and satisfy a set of constraints described in the previous section. The data available in making the decision for sustainable energy planning are summarized in Tables 2 and 3. As one may observe, three types of scenarios—basic, worst, and safe (in terms of the urgency of reducing the GHG emission and oil prices)—have been defined with probabilities of 0.6, 0.2, and 0.2, respectively.

4.2. Results

Robustly optimized solutions for the given case are illustrated in Figs. 3–5. Three different sets of solutions are obtained under different values of *w*, or the price of emission allowance: 13, 20, and 40 U.S. dollars per tonne of CO_2. In other words, the proposed model's robustness against infeasibility associated with meeting the emission requirement is tested.

Beginning with the current price of emission allowance ($13/tonne), it can be easily noted that oil plants are the sole type of power plants to be installed in all of subsequent years until 2020. This is mainly due to the fact that both investment and fixed costs for oil plants are the lowest among the alternatives (Table 2). Although their emission rate is among the top three and about two to seven times higher than ones for RES-based power plants, the price of emission allowance is not high enough to lower its

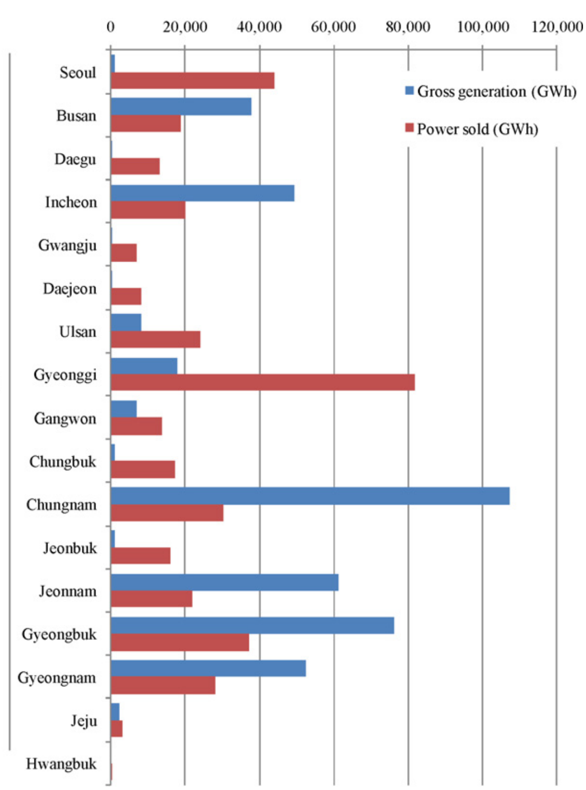

Fig. 2. Regional energy generation and consumption in South Korea during the year 2008.

Table 2
Costs, emission rates, initial capacities, and limiting potentials for power plants.

Plant type	Capital costs ($/MW)	Fixed costs ($/MW)	Emission rates (tonne/MW)	Initial capacity (MW)	Limiting potential (MW)
Coal	1,317,610	225	1965	18,678	–
Oil	652,720	74	1496	6128	–
Gas	793,270	118	1154	10,049	–
Nuclear	2,148,720	355	631	17,932	–
Biomass	2,252,780	720	2253	0	–
Hydro	3,266,330	858	234	351	1709
Solar PV	5,631,270	197	847	32	127,392
Wind	1,689,250	296	144	50	14,084

Table 3
Fuel costs and the required emission levels under varying scenarios.

Fuels ($/TOE)	Scenario	Year											
		2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Coal	All	97	97	97	97	97	97	97	97	97	97	97	97
Oil	Basic	99	97	95	93	91	89	87	85	83	79	75	71
	Worst	99	101	103	105	107	109	112	115	118	121	124	127
	Safe	99	92	87	81	75	69	63	57	51	46	40	35
Gas	All	145	145	145	145	145	145	145	145	145	145	145	145
Uranium	All	19	19	19	19	19	19	19	19	19	19	19	19
Biomass	All	130	130	130	130	130	130	130	103	130	103	103	103
Emission level (M tonne)	Basic	159.8	169.7	173.3	176.7	181.0	185.2	191.1	196.9	199.5	202.2	205.0	207.8
	Worst	142.0	150.8	154.0	157.1	160.8	164.6	169.8	175.0	177.4	179.8	181.6	184.7
	Safe	177.5	188.5	192.5	196.4	201.1	205.8	212.3	218.7	221.7	224.7	227.8	230.9

competitiveness. For the same reason, no CCS is to be installed either since its economics are mainly dependent on the allowance price. In fact, within the defined scenarios where the emission level required in the worst scenario needs to be 20% lower than the level required in the basic scenario, costs are minimized by purchasing emission allowances of volumes as large as 94 M tonne in year 2020 (Table 4).

Different solutions are obtained when *w* is changed to a higher value of 20 U.S. dollars per tonne of CO_2 (Table 5). Fig. 4 demonstrates that gas plants are to be added in the first 5 consecutive years, with oil plants taking the responsibility in the upcoming years. Two factors account for the enhanced competitiveness of gas plants under this hypothetical situation: costs, and the emission rate. From Table 2, it can be pointed out that gas plants rank the second in the increasing order of investment and fixed costs; despite their high fuel costs, total costs per unit capacity becomes the lowest. In addition, the emission rate of gas plants is approximately 30% lower than the rate of oil plants. Consequently, it becomes competitive enough to replace oil plants with a greater penalty for violating the emission requirement. In other words, for the first 5 years the rewards from reducing CO_2 emission are greater than cost-differences between oil and gas plants; however, a greater variance in oil prices for the subsequent years overcomes these differences such that oil plants are now employed instead of gas plants (Fig. 4).

Increasing the price of emission allowances further to $40/tonne results in a new set of plans. Unlike in the previous cases, wind, gas, oil plants, and CCS are to be installed in the coming years until 2020. First of all, wind plants are now competitive since they emit the least amount of CO_2 per TOE of energy generated; their costs are also the lowest among RES-based power plants. Consequently, they can minimize the costs with the addition of revenues from selling the emission allowances to neighboring regions. Meanwhile, gas and oil plants remain to be installed, as in the previous two cases, for the same reasons. Lastly, CCS is to be retrofitted to all existing capacities of coal plants since the revenues from trading emission allowances now overweigh their investment and fixed costs. It can be inferred that in this

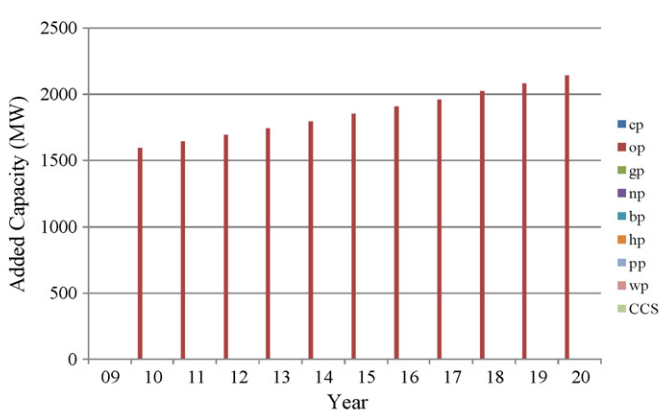

Fig. 3. Capacities to be installed when *w* equals to $13/tonne.

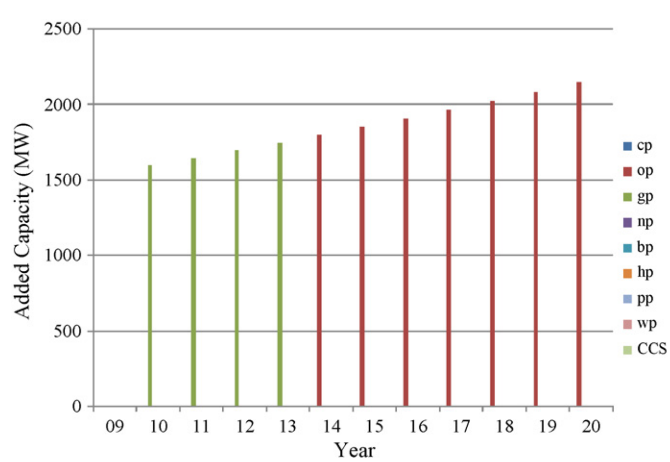

Fig. 4. Capacities to be installed when *w* equals to $20/tonne.

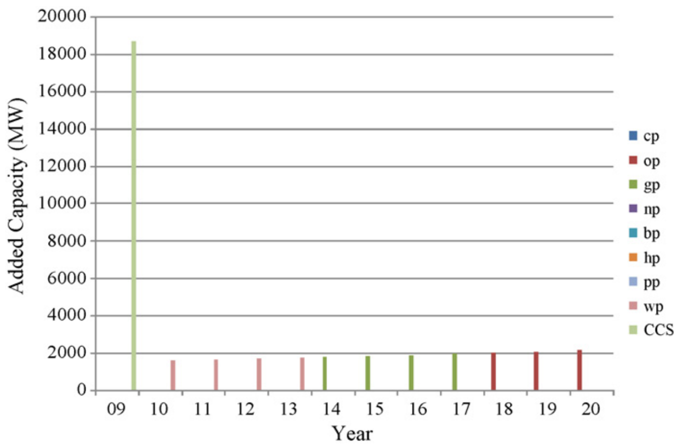

Fig. 5. Capacities to be installed when w equals to $40/tonne.

hypothetical case with w being $40/tonne the revenues and/or penalties from exchanging emission allowances becomes a dominant factor in minimizing costs. This is the precise reason why wind and CCS-retrofitted coal plants—the two types with lowest emission rates—are to be installed in this hypothetical case.

4.3. Sensitivity analysis

The proposed methodology performs a robust optimization of sustainable energy planning according to the method proposed by Yu and Li [17]. Under this method, the selection of numerical value for w determines decision makers' willingness to trade-off between solution and model robustness. In this study, solution robustness is measured by total costs of planning while model robustness is calculated in terms of underfulfillment of the emission requirement. Consequently, it becomes natural to select w as the price of emission allowances, or equivalently the additional costs decision makers need to pay due to emitting an excess amount of GHG, which in this case study is CO_2. Studying the role of w in the objective function through a sensitivity analysis can thus provide insights on effects that the price of allowances may have on total costs, and optimal plans. In fact, a valuable insight on the competitiveness of CCS can be understood from the analysis results in Fig. 6: there is a kink in the plots of total costs and the total volume of emissions trading when w is between 22 and 23 U.S. dollars per tonne. It is the price beyond which benefits of retrofitting CCS gained from trading reduced volumes of emissions surpass costs in retrofitting and maintaining them. As a result, total costs declines with higher prices of allowances. Although the exact price may vary according to the parameters

Table 4
Volumes of emissions trading that are expected to take according to the robustly optimized solutions when w equals to $13/tonne.

Scenario	Volume of emissions trading (M tonne)											
	Year											
	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Basic	33.1	29.9	33.2	36.7	39.9	43.2	45.1	47.3	52.9	58.7	64.6	70.8
Worst	50.9	48.8	52.5	56.5	61.0	63.8	66.4	69.2	75.0	81.1	88.0	93.9
Safe	15.4	11.1	14.0	17.2	19.8	22.6	23.9	25.5	30.7	36.2	41.8	47.7

Table 5
Volumes of emissions trading that are expected to take according to the robustly optimized solutions when w equals to $20/tonne.

Scenario	Volume of emissions trading (M tonne)											
	Year											
	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Basic	33.1	28.4	30.1	32.2	33.5	36.8	38.7	40.9	46.5	52.3	58.2	64.4
Worst	50.9	47.3	49.4	51.8	53.7	57.4	60.0	62.8	68.6	74.7	81.6	87.5
Safe	15.4	9.6	10.9	12.5	13.4	16.2	17.5	19.1	24.3	29.8	35.4	41.3

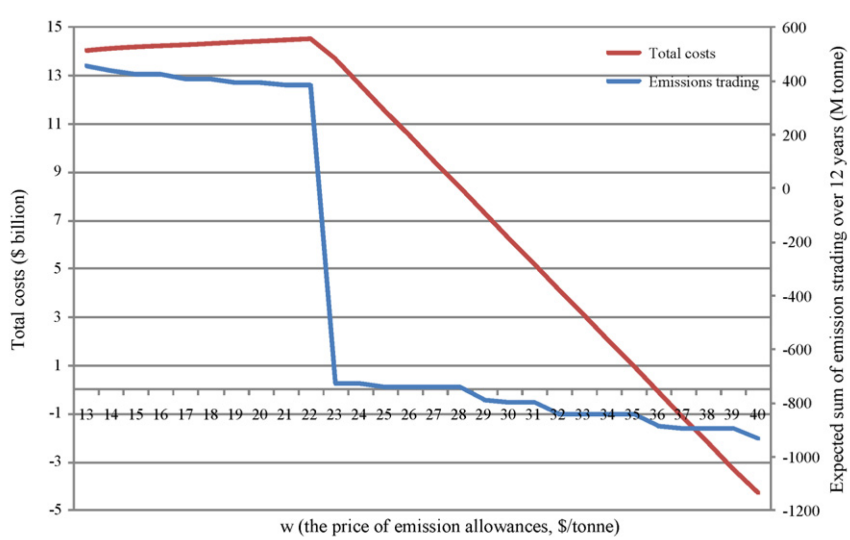

Fig. 6. Sensitivity analysis of optimization results in terms of solution and model robustness.

used, the analysis allows decision makers to determine the appropriate time and extent of retrofitting CCS.

5. Conclusion

In this paper, a new methodology for sustainable energy planning has been proposed. It generates robustly optimal solutions, or capacities of power plants to be installed, stripped, and/or retrofitted over a period of years. It is based on the modified EFOM, and minimizes total costs in planning under an uncertain environment where fuel costs and emission requirement levels may vary with respect to future scenarios; therefore, decision makers can lower risks due to a high volatility of uncertain parameters such as fuel prices. It also differs from the previous methodologies in that CCS is included as an available option for sustainable energy planning; they may be installed in fossil fuel plants if the price of emission allowances is high enough to compensate for their costs. In fact, decision makers may analyze sensitivity of results with respect to the price of allowances and thereby find out the most economical period and extent of CCS installation.

A case study has been presented to demonstrate applicability of the proposed methodology, as well as insights that it offers. According to the case study results, power plants that use fossil fuels are still more competitive than RES-based plants when the emission allowances are traded at the price of $13/tonne. However, wind power plants become more attractive as the price rises to the level of $20/tonne or higher; other RES technologies appear to need further reduction in capital costs to compete against CCS-installed plants that use fossil fuels. In this manner, the proposed methodology also offers insights on the appropriate price of emission allowances that will promote greater usage of RES and/or CCS technologies in sustainable energy planning.

References

[1] Cormio C, Dicorato M, Minoia A, Trovato M. A regional energy planning methodology including renewable energy sources and environmental constraints. Renew Sustain Energy Rev 2003;7:99–130.
[2] Cai YP, Huang GH, Yang ZF, Lin QG, Tan Q. Community-scale renewable energy systems planning under uncertainty—an interval chance-constrained programming approach. Renew Sustain Energy Rev 2009;13:721–35.
[3] Linkov I, Varghese A, Jamil S, Seager TP, Kiker G, Bridges T. Multi-criteria decision analysis: a framework for structuring remedial decisions at contaminated sites. In: Linkov I, Ramadan A, editors. Comparative risk assessment and environmental decision making. Kluwer; 2004. p. 15–54.
[4] Terrados J, Almonacid G, Pérez-Higueras P. Proposal for a combined methodology for renewable energy planning: application to a Spanish region. Renew Sustain Energy Rev 2009;13:2022–30.
[5] Dalia S. Comparative assessment of future power generation technologies based on carbon price development. Renew Sustain Energy Rev 2010;14:1283–92.
[6] Regnier E. Oil and energy price volatility. Energy Econ 2007;29:405–27.
[7] Laurikka H, Koljonen T. Emissions trading and investment decisions in the power sector—a case study in Finland. Energy Policy 2006;34:1063–74.
[8] Alphen KV, Noothout P, Hekkert M. Evaluating the development of carbon capture and storage technologies in the United States. Renew Sustain Energy Rev 2010;14:971–86.
[9] Leung SCH, Tsang SOS, Ng WL, Wu Y. A robust optimization model for multi-site production planning problem in an uncertain environment. Eur J Oper Res 2007;181:224–38.
[10] Grohnheit PE. Economic interpretation of the EFOM model. Energy Econ 1991;13:143–52.
[11] Jun SY, Lee SM, Park JW, Jeong SJ, Shin HC. The assessment of renewable energy planning on CO_2 abatement in South Korea. Renew Energy 2010;35:471–7.
[12] Soentono S, Aziz F. Expected role of nuclear science and technology to support the sustainable supply of energy in Indonesia. Prog Nucl Energy 2009;13:721–35.
[13] Huh C, Kang SG, Hong S, Choi JS, Baek JH, Lee CS, et al. CO_2 storage in marine geological structure: a review of latest progress and its application in Korea. Energy Procedia 2009;1:3993–4000.
[14] Gibbins J, Chalmers H. Carbon capture and storage. Energy Policy 2008;36:4317–22.
[15] Hansson A, Bryngelsson M. Expert opinions on carbon dioxide capture and storage—a framing of uncertainties and possibilities. Energy Policy 2009;37:2273–82.
[16] Rubin ES, Chen C, Rao AB. Cost and performance of fossil fuel power plants with CO_2 capture and storage. Energy Policy 2007;35:4444–54.
[17] Yu CS, Li HL. A robust optimization model for stochastic logistic problems. Int J Prod Econ 2000;64:385–97.
[18] Zini G, Tartarini P. Hybrid systems for solar hydrogen: a selection of case-studies. Appl Therm Eng 2009;29:2585–95.
[19] Azzopardi B, Mutale J. Life cycle analysis for future photovoltaics systems using hybrid solar cells. Renew Sustain Energy Rev 2010;14:1130–4.
[20] Khan MJ, Iqbal MT. Dynamic modeling and simulation of a small wind–fuel cell hybrid energy system. Renew Energy 2005;30:421–39.
[21] Jaramillo OA, Borja MA, Huacuz JM. Using hydropower to complement wind energy: a hybrid system to provide firm power. Renew Energy 2004;29:1887–909.
[22] Korea Electricity Power Corporation (KEPCO). Statistics of electric power in Korea. South Korea: KEPCO; 2009, http://www.kepco.co.kr.
[23] Lee S, Park JW, Song HJ, Maken S, Filburn T. Implication of CO_2 capture technologies options in electricity generation in Korea. Energy Policy 2008;36:326–34.